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Sport Action Mining: Dribbling Recognition in Soccer

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Abstract Recent advances in Computer Vision and Machine Learning empowered the use of image and positional data in several high-level analyses in Sports Science, such as player action classification, recognition of complex human movements, and tactical analysis of team sports. In the context of sports action analysis, the use of positional data allows new developments and opportunities by taking into account players' positions over time. Exploiting the positional data and its sequence in a systematic way, we proposed a framework that bridges association rule mining and action recognition. The proposed Sports Action Mining (SAM) framework is grounded on the usage of positional data for recognising actions, e.g., dribbling. We hypothesise that different sports actions could be modelled using a sequence of confidence levels computed from previous players' locations. The proposed method takes advantage of an association rule mining algorithm (e.g., FPGrowth) to generate displacement sequences for modelling actions in soccer. In this context, transactions are sequences of traces representing player displacements, while itemsets are players' coordinates on the pitch. The experimental results pointed out the Random Forest classifier achieved a balanced accuracy value of 93.3% for detecting dribbling actions, which are considered complex events in soccer. Additionally, the proposed framework provides insights on players' skills and player's roles based on a small amount of positional data.

Keywords Dribbling action detection · Soccer Analysis · Association rules · Machine Learning.

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1 Introduction

Action recognition in soccer analysis is a growing topic in Computer Vision and Sports Science due to the possibility of automatic scouting of soccer matches. Scouting plays an important role in soccer analysis since this task provides high-level information related to the tactical and technical aspects of the match under analysis, supporting the decision-making process of coaches and their assistants. In terms of tactical strategy, the dribbling action is paramount in a soccer match, since this action is used to solve tactical match problems (Lo et al. 2019; Leal et al. 2021) and can potentially help a player to create open space, and therefore opportunities for scoring (Moura et al. 2012). Nowadays, there are some companies in soccer analysis that provide scouting analysis on demand such as Stats Perform.[1] However, this service is quite expensive and there are no open source solutions for supporting sports performance analysis. In this context, the development of methods and tools to support automatic scout analysis has attracted a lot of attention from both academia and the sports industry.

The available methods proposed in the literature for human action recognition in soccer analysis usually try to recognize events (e.g., yellow and red cards, or even goal events) or well-defined actions, such as running, walking, or shooting (Giancola et al. 2018). Martin et al. (2020) introduced an efficient algorithm for producing mid-level representations of classic low-level key point-based feature descriptors such as histogram of oriented gradients (HOG), which was used to fed classification algorithms such as Support Vector Machines (SVMs) to build models capable for recognising actions as kicking, walking, running, among others. Baccouche et al. (2010) proposed an action recognition method to identify shot-related actions using bag-of-visual-word representations, based on SIFT features and LSTM-RNN networks to deploy a multi-class classification system to recognise the actions. However, the recognition of dribbling actions was not considered in both studies.

Targeting the recognition of dribbling actions, Tsunoda et al. (2017) introduced a deep-learning-based method to identify dribble, shoot, and pass actions in futsal matches. Their approach used an AlexNet network (Krizhevsky et al. 2012) and two hierarchical LSTMs (Gao et al. 2020) to recognise dribbling actions using a dataset containing only these three actions, i.e., without any distractors commonly found in real matches. For instance, action as conduction can potentially be misclassified as a dribbling event, an issue that was not taken into consideration in their study.

A promising initiative for analysing dribbling style was proposed by Li and Bhanu (2019). In their study, the authors introduced a method for detecting dribbling style. From the perspective of soccer analysis and sports science, this approach is relevant as it could help coaches and soccer experts in tasks related to the detection of talented players, which is an open problem and has gained the attention of several research groups around the world. However, a limitation of this approach relies on the fact that the proposed method assumes that dribbling events to be analysed were previously detected and segmented from the raw video stream, i.e., this method demands the previous use of methods that automatically detect dribbling actions in real soccer matches.

With this in mind, we propose in this work a novel framework for detecting sports actions from positional data, called Sports Action Mining framework (SAM). SAM was designed to provide general profiling and useful patterns to recognise sports-related actions based on the sequence of movements. SAM receives positional data from a tracking algorithm (De Barros et al. 2006) and provides insights on different sport action goals, such as recognition tasks able to support automatic scouting and skill modelling based on clustering computing. These outcomes are achieved by using a pipeline, grounded on association rule mining and machine learning algorithms, comprising data pre-processing, trace extraction, generation of association rules, action profiling, and recognition tasks.

The main aim of this work is to investigate the use of positional data for recognising dribbling actions, which is considered a complex movement in soccer. Under this perspective, we transform the action recognition problem, based on images and videos, into a pattern discovery problem in time series data. We believe that is our main contribution that differentiates our approach from the existing ones. We hypothesise that it is possible to model different sports actions using a sequence of confidence levels computed from previous players' displacements. The proposed method takes advantage of association rule mining algorithms for modelling actions in soccer. In other words, our framework can address the problem of automatically represent players and their displacements, which allows the extraction of patterns for further scouting and action recognition.

Traditional data mining methods have deficiencies when dealing with large redundancy probability and large error of approximation (Li et al. 2019b). These are important drawbacks found when dealing with positional data in a soccer field. In order to tackle these drawbacks, association rule mining algorithms can discover a small set of rules in a database using predefined minimum support and

[1] `https://www.statsperform.com/` (As of September 2021).

confidence from a given database (Gan et al. 2019). In soccer analysis, these algorithms are able to deliver reliable transcription of interactions among players displacements toward recognising sports actions. It is important to mention the recent use of association rule mining algorithms in a wide range of areas, such as health (Li et al. 2019b), cybersecurity (Kim et al. 2019), and energy (Li et al. 2019a), when the problem demands understanding and summarising in a large redundant scenario.

Particularly, we explored FPGrowth (Han et al. 2000), originally proposed for discovering frequent itemsets in a transaction database, to generate association rules. The association rules are checked towards providing the action feature vector. We investigated four machine learning algorithms (Support Vector Machine with the linear and radial kernel, Multi-Layer Perceptron, and Random Forest) for recognising dribbling in soccer based on the action feature vectors generated. Moreover, we explored the descriptive capacity of feature vectors related to dribbling actions by clustering them into a reduced search space.

Our framework allows automatic scouting and can be easily tailored to the creation of sports decision support tools as it provides a generic skill modelling solution for real-time recognition of sports actions, based on patterns defined in terms of a small amount of positional data, which are expected to be acquired on-the-fly. Precisely, our framework takes as input the positional data of a player, converting his location changes as transactions for obtaining association rules. These rules are probability-based, i.e., a sequence of displacements are encoded as a sequence of rules' probabilities throughout time. We then segment the probability sequence with the goal of extracting a feature vector. Our motivation is to use both trend and seasonality of probabilities to characterise relevant dynamic events, such as improvisation (periods of high and low confidence levels) and ordinary (sequences of high probability) events.

In summary, the main contributions of this work are:

- the proposal of a new framework using estimated positional data of players (location coordinates);
- a new approach for detecting dribbling actions automatically. To the best of our acknowledge, this was the first attempt to deal with the dribbling detection problem using the player's displacement in the pitch over time;
- validation of the proposed framework in classification and clustering tasks related to the detection and characterisation of dribbling events in soccer matches;
- a novel and comprehensive dataset to support dribbling detection, which was annotated by experts in Sports Science; and
- accurate performance (93.3%) for detecting dribbling actions using SAM and Random Forest.

The remaining of this text is organised as follows. Section 3 presents the proposed method for dribbling detection. Section 4 presents and discusses the experimental results. Finally, Section 5 provides our conclusions and outlines future research venues.

2 Related Work

Visual-based recognition is undoubted the most common approach to recognize actions in sports, especially in soccer analysis. Despite the advent of deep-learning-based in terms of visual understanding, the problem of recognizing meaningful actions for sports analysis is still an open problem, since the proposed approaches are able to recognize actions that may not be interesting under the perspective of sports science. At the same time, the recognition of complex actions in soccer has been overlooked mainly due to the lack of good-quality annotated data that requires a labor-intensive data annotation process, supervised by experts in soccer.

A considerable amount of research has been devoted to establishing the need for objective forms of analysis and their importance in the coaching process (Connolly and Grayson 2021). For soccer analysis, data about players' positions and technical actions (control, passing, running with the ball, dribbling, and shot-to-goal) may provide valuable information about teams' performance during a match. The major purpose of analysing a soccer match is to correlate the technical elements with the match score (Moura et al. 2014). Some studies relate data about patterns of build-up play, ball possession and number of shots to goal to the success in the result of the game (Tenga et al. 2010a,b).

Traditionally, such investigations were developed using hand and computerised notation systems developed by sports and computer scientists. Manual notational analysis, even when performed by trained analysts, has limitations. Such methods are high time consuming, subjective, and susceptible to human error and bias. Thus, automating sports movement recognition is an alternative to enhance both the efficiency and accuracy of sports performance analysis (Cust et al. 2019). A recent systematic review (Cust et al. 2019) in the sports context presented machine and deep learning techniques for movement recognition using inertial measurement unit (IMU) and/or computer vision data inputs. In another study, the video sequences and deep learning techniques were used to recognize accurately the actions of the ice hockey players (Vats et al. 2019). Similarly, Maddala et al. (2019) achieved success in yoga action recognition using traditional human action data from publicly available datasets.

There exist few datasets available in the literature that support two main tasks sports-related research: video recognition and action recognition. For the video classification task, there are large datasets available, such as UCF Sports (Rodriguez et al. 2008), Sports-1M (Karpathy et al. 2014), and SSET (Feng et al. 2020). The UCF Sports dataset comprises 150 sequences of ten types of sports (e.g., skateboarding, swing, and running), while Sports-1M dataset comprises one million YouTube videos belonging to 487 classes, including boxing, bicycle, tennis scenes, among others. In turn, the SSET is a heterogeneous datasets comprising 350 broadcast soccer videos (282 hours) along with three types of annotations: (1) scenes (e.g., far-view shot, playback, coach-view shot); (2) kick-related events such as corner, free-kick, goal, among others; and (3) players' bounding box locations.

For the action recognition task, there are few datasets that support soccer-related researches, such as MICC-Soccer-Actions-4 (Baccouche et al. 2010) and SoccerNet (Giancola et al. 2018) datasets. The MICC-Soccer-Actions-4 comprised 100 video clips of four different actions (shot-on-goal, placed-kick, throw-in, and goal-kick). On the other hand, the SoccerNet dataset is composed of 500 soccer games from six main European leagues, and contains three classes of events: goal, yellow/red card, and substitution. For further reading on the problem, we recommend the Cuevas's survey (Cuevas et al. 2020).

Although important progress has been achieved in the literature (Cioppa et al. 2020; Baccouche et al. 2010; Fakhar et al. 2019), the available events in the aforementioned datasets usually appear at the beginning or at the end of a sequence of actions (e.g., goal or yellow card after a fault). We believe that recognition of such events is a valuable soccer performance analysis, but the action that may happen during a sequence of actions is paramount to understand offensive and defensive plays (e.g., pass and dribble).

Some of the recent studies in the literature have focused on the identification and analysis of tactical behaviour, movement patterns, and styles of play. On the other hand, some researchers emphasised the tools to identify specific player's actions and performance, or relevant match situations. For instance, with the purpose of to reduce the subjectivity of classifying the quality of passes in soccer, Chawla et al. (2017) explored a model that constructs numerical predictor variables from spatiotemporal match data (i.e., players' tracking data and actions performed) using feature functions based on methods from computational geometry, and then learns a classification function from labelled examples of the predictor variables. The authors reported accuracy of 85.8% on classifying passes into three levels.

Decroos et al. (2017) proposed the POGBA, an algorithm for automatically predicting highlights in soccer matches from spatiotemporal match data as well. The algorithm predicts the probability that a given game state will lead to a goal, exploiting the insight that goals are preceded by goal attempts, which are much more frequent than goals. POGBA outperformed the baseline algorithms in terms of precision and recall. A similar proposal was presented by Janetzko et al. (2014) that reported a Visual Analytics method to cover single-player, multi-player, and event-based analytical views, finding the most important events in a match. Additionally, Stein et al. (2015) advanced the basic approach proposed by Janetzko et al. (2014) by introducing semantically-meaningful features, which allow an effective and interpretable exploration process, respectively. The authors improved the results of the classification accuracy and recall for interesting moments of the match, judged by experiments with a soccer expert.

Hosseini and Eftekhari Moghadam (2012) used a soccer broadcast video to detect different match situations that may happen during the video sequence. The authors presented a flexible system based on a fuzzy rule-based reasoning system which adopts statistical information from a set of audiovisual features to produce semantic concepts corresponding to the events. The tool was efficient in detecting actions, such as goals, saves, fouls, and corner kicks. When sequences of actions are the key-points of the analysis, some recent studies introduced techniques to identify teams' patterns and collective behaviour. Link et al. (2016) evaluated the attacking performance. The authors reported a quantitative representation of the probability of a goal being scored for every point in time at which a player is in possession of the ball.

Finally, the study of Stein et al. (2019) proposed a novel method for the semi-automatic definition and detection of events based entirely on the movement data of players and the ball. Using Allen's interval algebra integrated with a visual analytics system, the authors enable analysts to visually define, as well as search for complex and hierarchical events. The tool was efficient in detecting several events, such as passes, player running with the ball, goal, and crosses.

Although the studies mentioned provided valuable and efficient tools for event detection as well as key moments of the match, there are some important issues to take into consideration. Most of them require video as input to identify events and action sequences, in which the amount of information to process is a limitation. On the other hand, for broadcast videos, the lack of information on the actions of the players that are not framed in the image. Other studies did not use video as input but players' tracking data, event annotations, and ball tracking data. Event annotations are very susceptible to rater subjective evaluation and bias, and are time-consuming procedures. Moreover, ball tracking is still a challenge and few studies reported low-cost alternatives to gather data. In this sense, our proposal is innovative because it requires only players' 2D position over time, common data collected by the analysts' staff of professional soccer clubs. Thus, our proposal focused on dribble detection using only players' positional information.

This research aims to fill existing gaps in the literature by proposing a novel framework that combines data mining and machine learning approaches to automatically detect dribbling actions in real matches played by professional soccer players. To the best of our acknowledge, that is the first attempt to deal with this problem. Our approach takes advantage of a spatiotemporal analysis to distinguish dribbling actions from other actions that may appear similar to a dribbling action such as running and running with the ball. Our algorithm takes as input players' displacements on the pitch over time, i.e., the (x,y) coordinates for each instant of time t, instead of analysing the video content of the matches, which is described in the section in detail. As there is no dataset available for detecting dribbling actions available in the literature, we created a dataset containing $1,966$ examples annotated as dribbling and non-dribbling actions, which were collected from twelve teams participating in the São Paulo State championship, and Brazilian championship, the premier league in Brazil (see Section 4.1 for more details).

3 Proposed Approach

This section presents the proposed method for detecting dribbling actions. Figure 1 shows the main steps of our framework, which is described, in detail, in this section.

SAM addresses the transformation of positional data into feature vectors capable of describing sport actions. This module comprises Pre-processing, Trace Extraction, Association Rule Generation, Action Profiling, Modelling, and Recognition components. The latter step allows the execution of vast recognition tasks based on players' action profiling generated by the SAM framework. For instance, our framework supports machine learning classification using the feature vector composed of confidence level scores associated with actions. Furthermore, clustering algorithms can take advantage of the similarity of actions to support the decision-making process based on the identification of common properties of clusters or the detection of anomalous movements.

Our proposal is grounded in the extraction of associations rules from a stream of positional data. A single trace regards a movement. A sequence of movements is associated with a rule that has its probability of occurrence computed. When estimating a sequence of probabilities, a sport action can be characterised and then recognised. In this work, we validate our framework for dribbling events. We claim that the variation of probabilities throughout a time window models the player improvisation, revealing a dribbling action.

3.1 Pre-processing

This step concerns the pre-processing of a dataset of spatial positions acquired from a given player during a match. Moreover, a sub-sampling strategy (e.g., K-fold down-sampling) is used to reduce the number of samples and their representation to obtain a computationally efficient feature extractor without compromising the description of actions. The formal definition of a K-fold down-sampling is shown in Eq. 1 where K is the integer down-sampling amount for input S and n the sample index. In other words, it is selected the samples following n.K index.

$$S_1[n] = S[n.K] \tag{1}$$

For example, using $K = 2$, we are able to select only the odd indexes from a sequence. The outcome of this step is a stream S_1 of p samples sorted by timestamp, $S_1 = [(x, y)_1, (x, y)_2, ..., (x, y)_p]$.

The pre-processing setup is strictly related to positional data technology. Sup-sampling needs to be tuned according to the frequency of positional data ingestion towards providing a suitable representation of player displacement and enriching the quality of data for further steps.

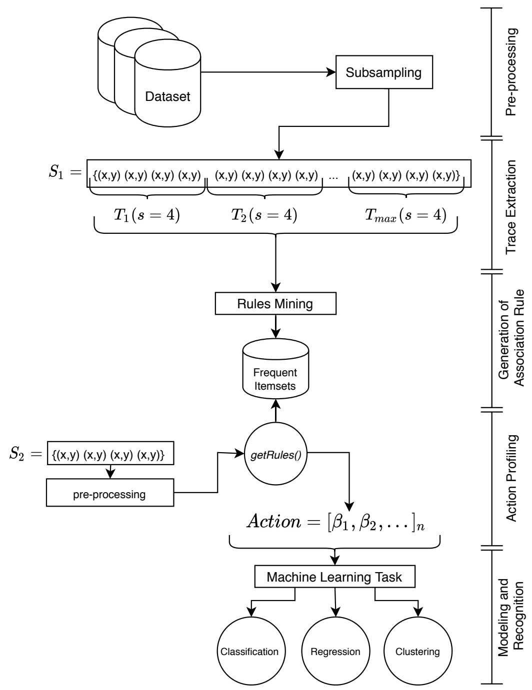


Fig. 1: SAM overview. Given a sequence of positional data from players and the ball, our framework performs a pre-processing procedure towards improving the signal quality. Then, we transform the positional data into chunks, named as trace, by windowing the improved positional data. Next, the extracted traces are used as input to the FPGrowth algorithm, which aims to discover the sample frequencies and to identify frequent samples. Finally, the feature vector composed of n confidence levels (β_i in the figure) can be used for modelling and recognition tasks, e.g., classification, regression or clustering.

Algorithm 1 windowing

Input:
s: Number of samples from each trace;
S: Stream of samples.
Output:
$Transactions$: Array of extracted traces.

```
Transactions ← [.]
n ← 1
for i ← 1 to |S| do
    T_n ← coordinates from S[i] to S[i + s]
    Transactions[n] ← T_n
    n ← n + 1
    i ← i + s
end for
```

3.2 Trace Extraction

Trace extraction transforms the stream of positional data into chunks (traces) capable of representing the movements in a soccer match, presented in Algorithm 1. A trace T is extracted from S_1 by $windowing(S, s) = [T_1, T_2, ..., T_{max}]$, where s is a hyperparameter related to the number of samples that compose each trace and max the maximum number of possible traces ($max = \frac{p}{s}$). A trace $T = [(x, y)_1, (x, y)_2, ..., (x, y)_s]$ is addressed as a transaction for obtaining association rules.

3.3 Generation of Association Rules

Association rule mining provides algorithms and tools to recognise patterns in data based on features that occur together and are correlated. Knowledge discovered is explained by means of rules, while some measures (e.g., support, confidence, and lift) associated with such rules can reveal their effec-

Algorithm 2 Generation of Association Rules

Input:
δ: Support threshold;
α:Minimum probability;
$Transactions$: Array of traces.
Output:
$rules$: Association rules.

$freq_T \leftarrow$ getFrequentPatterns($Transactions, \delta$)
$rules \leftarrow$ getAssociationRules($freq_T$,α)

tiveness. Support is related to historical data capacity to establish a rule; confidence, how a certain rule works, and the lift is the ratio between confidence and support. There are several algorithms for association rule mining, such as Apriori (Agrawal et al. 1994), FPGrowth (Han et al. 2000), Predictive Apriori (Scheffer 2001), FPMax (Grahne and Zhu 2003), DC-miner (Chengyan et al. 2020), and FIUFP-Growth (Thurachon and Kreesuradej 2021). The input is a collection of transactions (in this work, a collection of T), and each transaction contains one or more items (i.e., positional data) obtained from a stream of items (Raghunathan and Murugesan 2010). In Algorithm 2, as in (Han et al. 2000), it is possible to observe a general method to obtain association rules from transactions and their relationship with support and minimum probability.

Taking advantage of an association rule mining algorithm, it is assumed that transactions are a sequence of traces representing player displacements. The most frequent samples from the traces, with a given confidence, compose the dataset of Frequent Itemsets. Thus, given a stream of transactions, it is possible to calculate the sample frequencies and identify frequent samples and their confidence level.

FPGrowth is a popular and highly efficient frequent item-set mining algorithm grounded on a prefix tree representation of transactions (Borgelt 2005). This tree, named FPtree, can reduce memory when storing the transactions and provide prune strategies. First, the algorithm starts tracking the database once to find all frequent 1-itemsets to rank them in descendent order to drop the infrequent items. A given item (or an itemset) is considered infrequent when the number of transactions that contain this item is smaller than a minimum support threshold (δ). Next, the items in each transaction are sorted according to the previous rank bypassing the infrequent items. The frequent items are inserted in the FPtree by merging the transactions grounded in the corresponding prefix and following the same order, thus the FPtree is never bigger than the dataset processed. The confidence level of a rule is computed using the percentage of transactions that contain $itemset_a$ that also contains $itemset_b$. FPGrowth can filter the transaction outcomes based on a threshold of minimum confidence (probability) level, named as α.

Table 1: Summary of main features of the dataset used in this work.

Match	**Championship**	**Year**	**Number of Players**						**Dribble**	**Non-Dribble**
			DF	**FN**	**DF**	**MD**	**MD**	**FW**		
Team A × Team B	Brazilian Series A	2008	7	4	5	4	6		144	141
Team A × Team C	Brazilian Series A	2008	7	5	4	5	5		73	129
Team A × Team D	Brazilian Series A	2008	6	4	5	5	5		32	140
Team E × Team F	Brazilian Series A	2016	4	5	3	8	6		57	133
Team E × Team G	Brazilian Series A	2016	4	4	4	10	4		86	148
Team E × Team H	Brazilian Series A	2016	4	4	4	9	5		72	126
Team E × Team I	Brazilian Series A	2016	5	5	3	10	3		96	142
Team J × Team K	São Paulo State 2nd division	2014	4	5	4	6	7		113	128
Team J × Team L	São Paulo State 2nd division	2014	4	5	4	6	6		62	144
Total									**735**	**1,231**

3.4 Action Profiling

A sports action is grounded on a sequence of probabilities from generalised association rules. Given a stream of samples, called S_2, the feature vector of a sport action is composed of n confidence levels (β), $Action_{S_2} = [\beta_1, \beta_2, ..., \beta_n]$. Each β is the confidence level obtained by checking S_2 samples

Algorithm 3 Action Profiling

Input:
S_2: Stream of samples;
$rules$: Association rules;
s: Number of samples of each trace.
K: Frequency in Hz of S_2
Output:
$Action$: feature vector of confidence levels (β).

```
A ← [.] empty array of float
current ← 0
i ← 0
n ← 0
while i < |S2| do
    moment ← i
    while moment < i + s do
        if getRules(moment) == 0 then
            A[current] ← 0
        else
            A[current] ← getRules(moment)
        end if
        moment ← moment + 1
        current ← current + 1
    end while
    βn ← getMeanOf(A)
    Action[n] ← βn
    A ← [.]
    current ← 0
    n ← n + 1
    i ← i + K
end while
```

in Frequent Itemsets dataset for a particular moment, as demonstrated in Algorithm 3. Thus, the feature vector is a resource capable of explaining some particularities of sport actions by profiling the confidence of a player displacement sequence. In Algorithm 3, each sample (moment) from S_2 has its rule extracted by function *getRules()*. This function seeks for all rules started by the spatial coordinates of the inputted moment. Taking the sought rules, it is picked just the rules that match the next moment, satisfying a particular displacement. The output of getRules() is the displacement confidence level. In the case of no rule matching, the outputted value is zero. The value of n is related to the number of itemsets (displacements) required to represent a specific sport action.

Figure 2 illustrates a sequence of β (from β_{16} to β_{41} related to a dribbling action. It is important to mention the confidence levels inside the dribbling action interval present a disturbance, reaching a minimum confidence level on β_{30}, followed by a growth of confidence level. We assume the reduction of confidence levels is straightly related to an improvised action. When the improvised action follows a detected pattern, we are able to recognise a dribbling event. We then take advantage of machine learning algorithms to model the sequence of confidence levels as features and provide the automatic classification/clustering of the sport action performed in the interval.

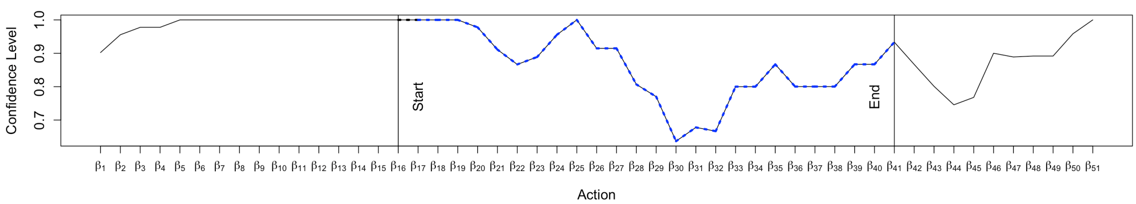


Fig. 2: Dribbling profile example, from β_{16} to β_{41}.

3.5 Recognition Tasks

The recognition step aims to discover meaningful patterns considering the use of machine learning algorithms and the action profiling data associated with players' displacement sequences. We can model the recognition task as a supervised or unsupervised learning problem since the early stages of the recognition step proposed in this work (i.e., trace extraction, the generation of association rules, and the computation of action profiling of players) are performed in an unsupervised manner. Examples of possible learning problems that could take advantage of our methodology include automatic scouting of some target sports actions performed by individual players (e.g., passes, dribbles) or by the team (e.g., defence and attack construction).

In this work, we focused on the analysis of dribbling actions considering two formulations for this problem. In the first formulation, we used unsupervised learning algorithms to perform a cluster analysis to understand the structure of the data and to cluster players with similar dribbling abilities. In the second formulation, we consider the use of supervised learning algorithms to detect dribbling actions automatically. For this, we built a dribbling action profiling dataset composed of dribbling and non-dribbling actions, whose annotations were performed by experts in soccer performance analysis (see Section 4.1).

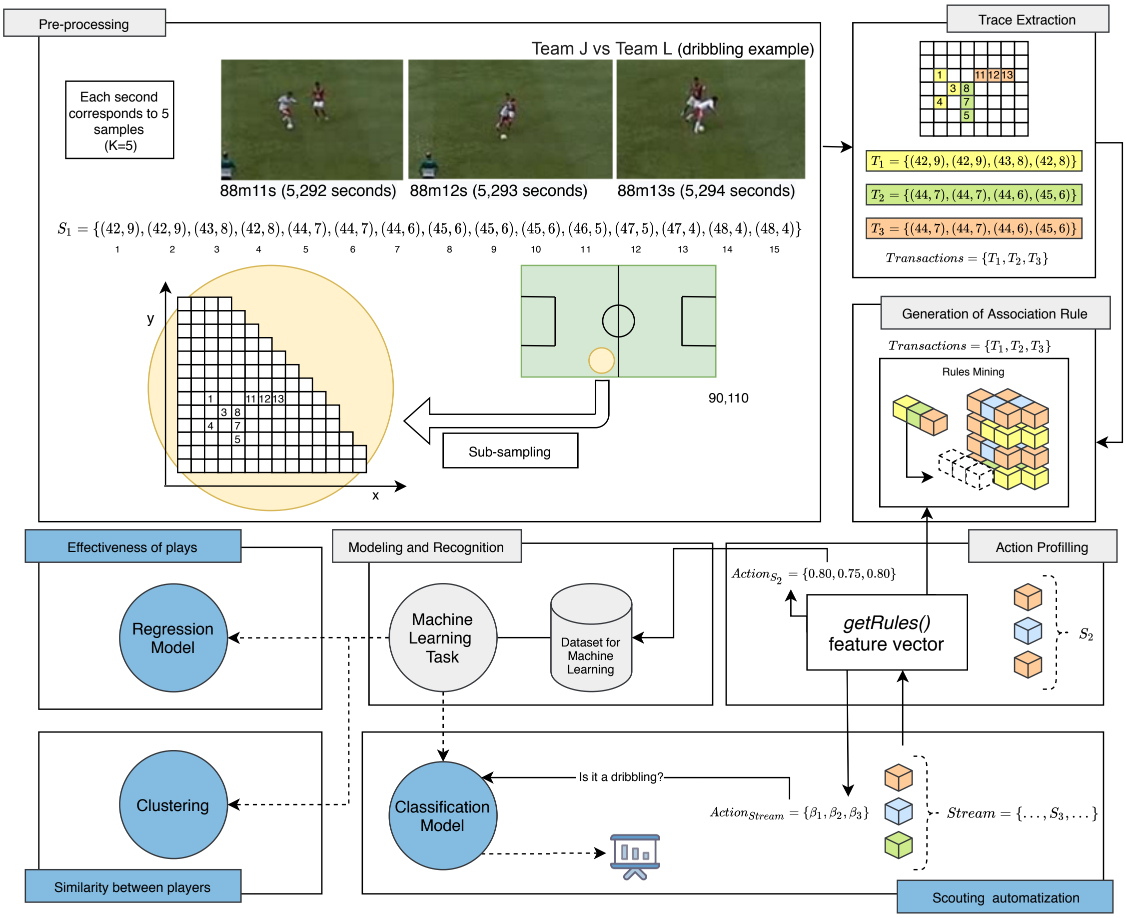


Fig. 3: SAM example, from a dribbling sample to generate the association rules towards machine learning tasks to provide the analysis of the effectiveness of plays, the similarity between players, and scouting automatisation.

4 Experiments and Results

In this section, we present the datasets and evaluation protocols used to validate the framework introduced in this paper (Sections 4.1 and 4.2), and the experiments designed to verify the effectiveness

Table 2: Description of parameter of the proposed methods whose values were fixed during the experiments.

Method's parameters	Value	Description
K	5	Down-sampling (sub-sampling)
p	13,792 – 15,056	Length of sample stream (S)
δ	2	Support threshold (FPGrowth)
α	0.5	Minimum probability (FPGrowth)

of our framework considering the problem of detecting dribbling actions. We model this problem in an unsupervised and supervised fashion. In the unsupervised learning approach, we used a clustering algorithm to find similar groups of dribbling actions, considering the action profiling of players generated by the proposed framework (see Section 4.3). More precisely, we are interested in whether there is some pattern in the way players from different positions perform dribbling actions.

In the supervised learning approach, we model the problem of detecting dribbling actions as a binary classification problem considering the classes dribble and non-dribble (see Section 4.4). In this case, we adopted the use of classification algorithms to build a machine learning model to automatically detect dribbling events in a match by classifying the actions as dribble and non-dribble.

4.1 Dataset

The dataset is composed of nine matches from three different Brazilian professional soccer teams in two different championships between the years 2008 and 2016. All data collected from players' displacements were acquired with 30 Hz. These data were generated by using an automatic tracking system, the DVideo software (Figueroa et al. 2003; Barros et al. 2007), from multiple calibrated camera video streaming, which provides the (x,y) coordinates of players in the pitch over time, besides their teams. The annotation of players' actions as dribbling and non-dribbling was performed by experts who are PhDs in Physical Education. The main challenge associated with this annotation process relies on the difficulty in the event annotation since the movements required to accomplish this action may appear similar to other actions as running and one-to-one confrontation (Leal et al. 2021). In this work, we consider the definition of dribbling proposed by Cunha et al. (2011), which states dribbling action as "an act of deceiving the opponent to get rid of his mark and facilitate the execution of other actions." Table 1 shows details of the dataset used in this work.

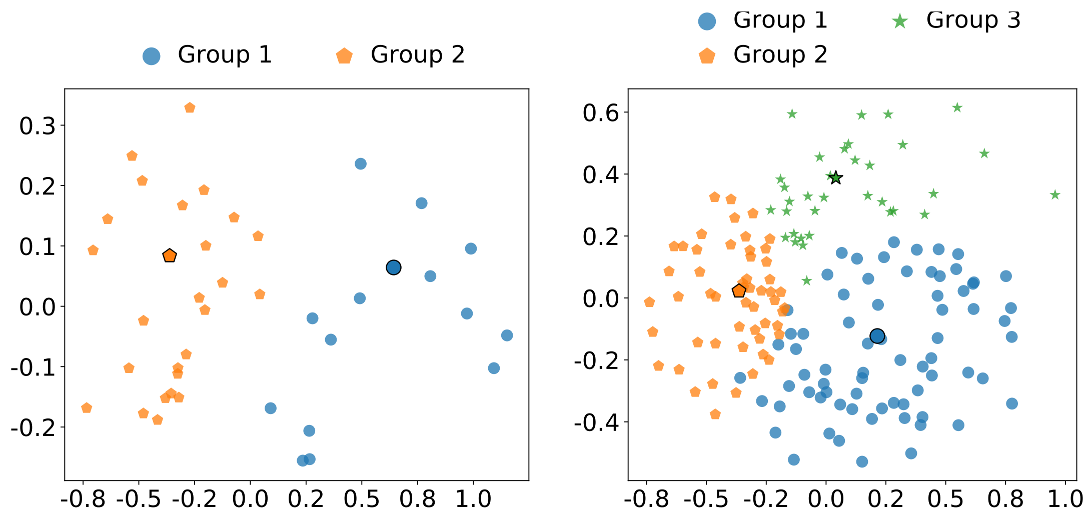
4.2 Experimental Setup and Protocol

For reproducibility purposes, this section presents the parameters whose values are constant during the experiments. In the pre-processing step, the video frames were down-sampled by 6 and used p samples, as shown in Table 2. The p value was chosen to standardise the stream length towards obtaining the maximum data of the same player in the field since a player can be substituted or excluded.

In this work, we choose FPGrowth as it is a widely-used approach given its better computation efficiency compared to the commonly used Apriori algorithm. Recall that the use of a more effective rule mining algorithm would potentially lead to even better results than those reported in this paper.

Given a stream of transactions, it is possible to calculate the sample frequencies and identify frequent samples using a support threshold (δ) and minimum confidence (α). It is important to mention that the obtained rules have a number of samples ranging from 2 to s. Also, considering that we explore the probability sequences of rules, different thresholds do not sharply affect the performance of our proposal. For example, if a sample appears 3 out of 5 traces, it has a support of $\frac{3}{5} = 0.6$, δ is related to setup a minimum support value to be used. On the other hand, α controls how often an association rule needs to be detected for composing the Frequent Itemsets dataset. For example, if in trace T_1, a set of samples appears 4 times and, T_1 and T_2 co-occur only 2 times, the confidence for the rule $T_1 \geq T_2$ is then $\frac{2}{4} = 0.5$.

We report the quality of obtained results considering the Balanced Accuracy (BACC), the Area Under the ROC Curve (AUC), Recall, Precision, and F1-Score measures. We adopted the k-fold cross-validation protocol ($k = 10$) to evaluate the classification models built using the following machine learning algorithms: Support Vector Machine (SVM) with both linear and radial basis functions as



(a) Defender players.

(b) Forward players.

Fig. 4: Cluster analysis considering the dribbling actions performed by defender (a) and forward (b) players.

kernel, Random Forest (RF), and Multilayer Perceptron (MLP) algorithms. After randomly splitting the dataset into ten folds, we performed a grid search on the training data to find the best hyper-parameters' values for the machine learning algorithms investigated in this work. The final results were reported considering the average (μ) and standard deviation (σ) of the results obtained on each testing fold. The code is publicly available.[2]

4.3 Unsupervised Learning: Cluster Analysis of Dribbling Actions using the Actions Profiling of Players

This section presents the results of a cluster analysis considering the action profiling of players built with our framework. We believe that the action profiling of players produced by our framework could allow us to find patterns of dribbling actions and group players with similar skills. Such analysis could be applied in training practices, helping trainers to find players with complementary skills and thus defining specific match strategies given by the skills of players.

In this analysis, we adopted the use of the Agglomerative Hierarchical Clustering algorithm (Duda et al. 2000) that finds clusters in a bottom-up fashion. In this context, the clustering algorithm starts clustering the data by taking all data points as an individual cluster. Then, the algorithm tries to find groups that increase a given objective function, defined by a linkage criterion, as minimum as possible. In this work, we used the Euclidean distance as a measure of similarity and Ward's method (Jr. 1963) as a linkage criterion, which minimises the total within-cluster variance. We also used the silhouette score (Rousseeuw 1987) to define the optimal number of clusters. Figures 4a and 4b show the clusters found considering the actions performed by the defender and forward players, respectively.

Figures 5 and 6 show examples of dribbling actions that represent the groups found by the clustering algorithm, from which we could observe different styles of dribbling actions. Figure 5a shows a dribble in which the player conducts the ball by changing his direction smoothly, while Figure 5b illustrates a dribble in which the player changes his direction more abruptly, in comparison with the first example. Similarly, Figure 6a shows a dribble action in which the player also changes his direction, while Figure 6b presents a dribble in which a player performs a one-to-one confrontation to dribble the opponent. Finally, Figure 6c illustrates an example in which the player's opponent tries (and fails) to intercept the ball.

We could observe that the dribbling actions aforementioned presented some peculiar patterns that distinguished them. For instance, the action presented in Figure 5a may appear similar to running events. However, the approaching of the adversary and the changes in the players' direction are elements that enable us to distinguish this dribbling style from the running action (Leal et al. 2021).

[2] `http://www.uel.br/grupo-pesquisa/remid/?page_id=145` (As of September 2021).

(a) Group 1

(b) Group 2

Fig. 5: Example of dribbling actions from the two groups found after clustering actions performed by defender players.

(a) Group 1

(b) Group 2

(c) Group 3

Fig. 6: Example of dribbling actions from the three groups found after clustering actions performed by forward players.

Furthermore, this result corroborates with Li's work (Li and Bhanu 2019), which consider there exist different dribbling styles in soccer. Finally, these results reinforce the quality of the collected data, in terms of diversity, which considers dribbling actions in different situations.

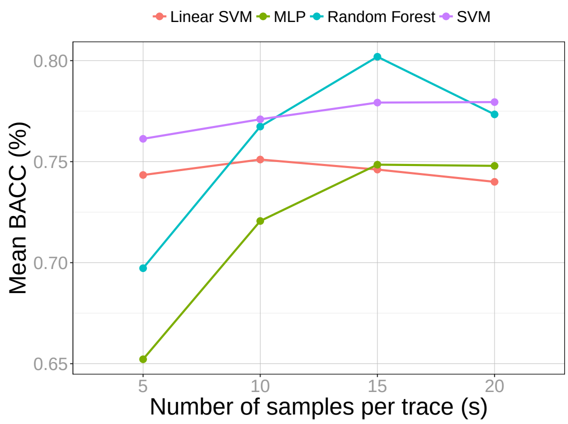


Fig. 7: Average of balanced accuracy values obtained by each classifier trained with feature representations generated with different values for the parameter s.

Table 3: Description of the parameter space of our proposed method.

Method's parameters	Value	Description
s	From 5 to 20, with a step size of 5	Number of samples per trace (T)
n	From 3 to 27, with a step size of 2	Length of feature vector for dribbling

4.4 Supervised Learning: Dribbling Actions Detection

We presented the results for the dribbling action detection problem considering two experimental sections. First, we performed an analysis of the parametric space to find the best configuration of our framework, and then we presented the performance results of our framework considering its best configuration. In this way, we could have a better comprehension of the robustness of our proposed methods, i.e., its behavior when we vary the parameter values (see Section 4.4.1). Next, we show the best performance achieved in each metric, i.e., the best configuration of our method that maximizes its performance on each metric considered in this work. This perspective shows how promising is our framework in different applications, considering that the adoption of the metrics depends on the target application (see Section 4.4.2).

4.4.1 Finding the Best Parameter Values for the Proposed Methods

Besides the parameters presented in the previous section and whose values were fixed as showed in Table 2, we investigate the behavior of our method considering a parameter space as described in Table 3. As we mentioned in Section 3, the parameter s refers to the number of samples in each trace extracted from the positional data stream, while the parameter n refers to the number of confidence levels obtained by checking an input stream for testing in the Frequent Itemsets dataset.

Figures 7 and 8 show the behaviour of the classification algorithms in terms of balanced accuracy, when we consider the parameter space presented in Table 3. From this experiment, we could observe that those classification models presented a better performance in terms of balanced accuracy, when we consider 15 samples per trace, except for the support vector machine algorithm, which presented a better performance when we have 20 samples per trace. In this case, we observed an increase of 3.4 percentage points. The other classifiers presented decreases of up to 8.44 percentage points (see the Random Forest results) by comparing the performance of classifiers using 15 and 20 samples per trace.

The number of confidence levels that compose the feature vector used to build the machine learning models also presented an important role in the overall performance of classifiers (see Figure 8). We could observe the Linear SVM classifier presented a more stable performance, while Random Forest and MLP classifiers reached the best performance when we model the actions using 13 confidence levels. Note that the Action Modelling step (see Figure 3) produces a feature vector containing confidence levels, which is used to feed the machine learning algorithm. The SVM classifier was the

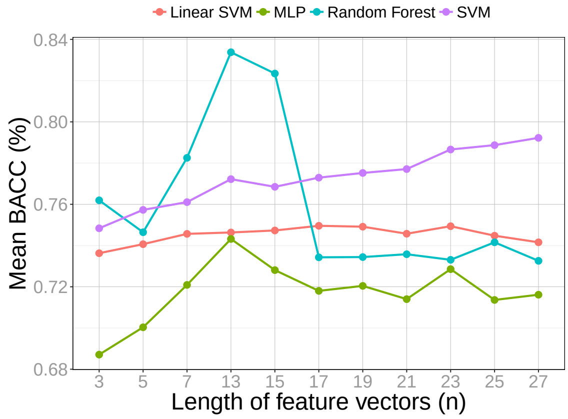
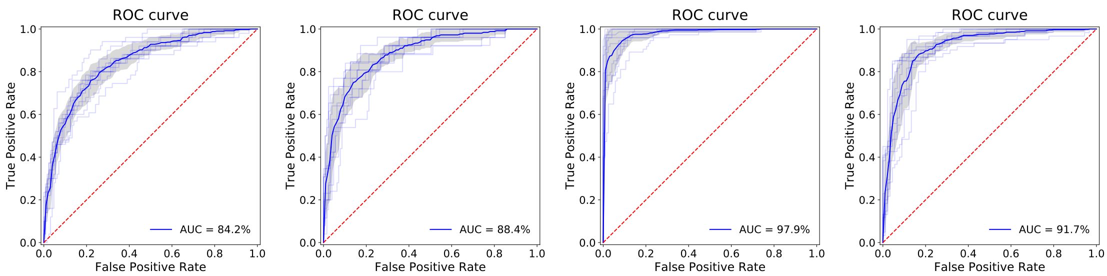
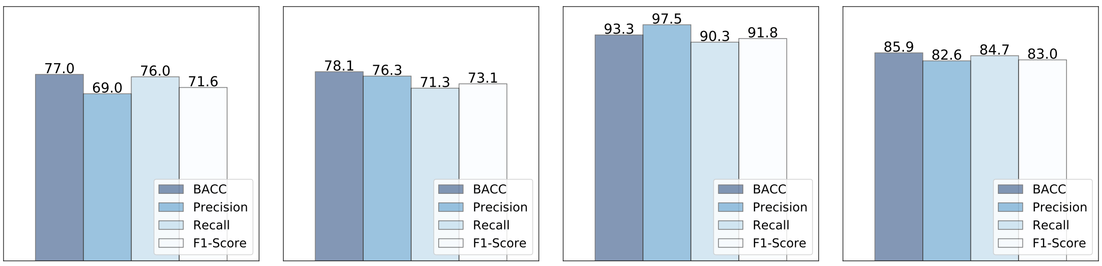


Fig. 8: Average of balanced accuracy values obtained by each classifier trained with feature representations generated with different values for the parameter n.



(a) Linear SVM (b) MLP (c) Random Forest (d) SVM

Fig. 9: Receiver Operating Characteristic Curve (ROC curve) for the classification algorithms, considering the best models achieved in this work in terms of AUC. The average curve is shown in dark blue and the shading around the average curve represents the standard deviation of performance results achieved in each testing fold.



(a) Linear SVM (b) MLP (c) Random Forest (d) SVM

Fig. 10: Performance results of classification algorithms used in this work, considering their best configuration for each metric. The results are in terms of average and standard deviation of testing on the 10-folds cross-validation protocol.

only algorithm whose performance kept improving by increasing the parameter n, i.e., the number of confidence levels (see Table 3). However, the latency of the proposed method increased significantly as we increased the parameter n. Thus, we believe there is a trade-off between efficiency and effectiveness aspects that needs to be taken into consideration during the tuning of this parameter. Finally, Table 4 shows the average and standard deviation of the performance results obtained on each testing fold, in terms of BACC, Precision, Recall, and F1-Score. These results confirmed the superiority of the Random Forest algorithm in comparison to other algorithms considered in this work.

Table 4: Performance results (%) of the proposed method in terms of average and standard deviation of testing on the 10-folds cross validation protocol.

Classifier	BACC	Precision	Recall	F1-Score
Linear SVM	77.0 ± 2.7	50.9 ± 2.6	75.0 ± 6.1	60.6 ± 3.1
MLP	78.1 ± 2.1	75.6 ± 4.8	69.4 ± 6.1	72.1 ± 2.8
Random Forest	93.3 ± 5.5	93.5 ± 4.7	90.3 ± 9.0	91.8 ± 6.7
SVM	85.9 ± 3.7	82.6 ± 4.4	83.6 ± 5.7	83.0 ± 4.5

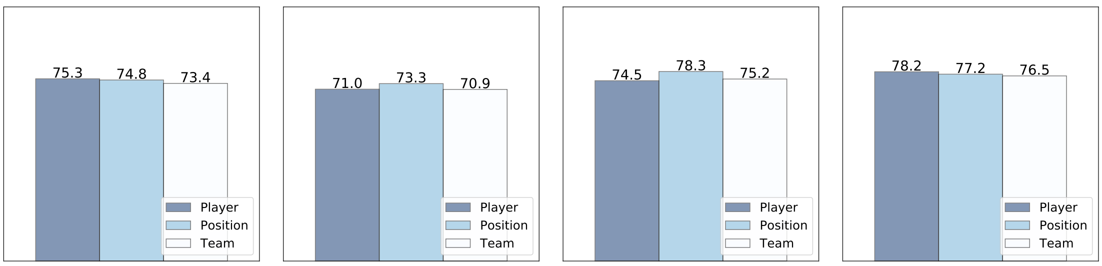
4.4.2 Comparison among the classification algorithms

This section presents a comparison of performance among the classifiers investigated in this work. Figure 9 shows the average ROC curves obtained for each classification algorithm. The average curves (in dark blue) were computed considering the performance of the models on each testing fold (in light blue). The shading around the average curve represents the standard deviation. We could observe an AUC of 97.7% for the Random Forest classifier and an AUC of 91.7% for the SVM classifier. Finally, Figure 10 shows the average of performance results obtained on each testing fold, in terms of BACC, Precision, Recall, and F1-Score, considering the best model for each metric. Again, the Random Forest presented the best performance for all metrics considered in this work, followed by the SVM classifier.

4.4.3 Dribbling Action Detection Between Different Player's Positions and Teams

This experiment aimed to evaluate if there are differences in detecting dribbling actions when we take into consideration three different perspectives: team, position, or players. In the first case, our framework extracted rules considering all players, which decreased the probability of having rules that encode the specificities of players and positions. However, our framework encodes features of a more "generic dribble." In turn, when we consider positions or players, the SAM framework encodes features of dribbling actions that are specific to the player position, for instance, long dribbling toward the goal line usually performed by left and right full-backs players, or short dribbles usually performed by the forward players.

Figure 11 shows the performance results for each classifier when trained using association rules generated with dribbling actions grouped by Player, Position, and Team. We could observe that Random Forest and MLP classifiers presented a better performance when the association rules generation took into consideration the positions of players. On the other hand, the SVM classifiers, for both linear and radial basis function kernels, presented a better performance considering the association rules generated by all players, regardless of their position or team. These results suggest that SVM classifiers are more sensitive to encoding features that are specific to the position, which may explain the worse performance for detecting dribbling actions in a more general way.



(a) Linear SVM (b) MLP (c) Random Forest (d) SVM

Fig. 11: Average of balanced accuracy values obtained by each classifier considering association rules generated with training examples of dribbling actions grouped by position, team, or players.

Fig. 12: Example of a true positive case of dribbling action detected in the match Team J (white shirt) vs. Team L (red shirt) at 88 minutes and 11 seconds.

Fig. 13: Example of a false positive case of dribbling action detected in the match Team J (white shirt) vs. Team L (red shirt) at 74 minutes and seven seconds.

4.5 Visual assessment

This section shows examples of hit and missed testing samples and further insights provided by the proposed framework. We believe this visual inspection could give us some direction regarding the failure patterns of the proposed method. Figure 12 shows a sequence of three scenes related to dribbling detected correctly. This action occurs in the match between Team J (white shirt) and Team L (red shirt), at the 88th minute. It is possible to observe an abrupt change of direction of the player that conducts the ball, our mapped player.

Conversely, in Figure 13, we can observe a sequence of images related to an action misclassified as dribbling in the match between Team J (white shirt) and Team L (red shirt) at the 74th minute. We believe this incorrect classification is related to the movement performed by the mapped player since the sudden displacement change was very similar to a dribbling sequence. Indeed, the player's ability to sprint with the change of direction manoeuvres predicts dribbling performance in soccer (Wilson et al. 2019). Thus, we can deal with this specific case using the information of opponent players or improve the association rule by taking advantage of ball conduction information.

It is important to mention that the frequent itemsets dataset is an enriched source of compiled information able to support strategic decisions on-the-fly. Observing this dataset, it is possible to recognise common plays, successful strategies, and players with similar performance. Figure 14 shows the most frequent dribbling from a left side full-back player. This specific dribbling reveals a successful displacement able to open the opposite defence towards producing a goal opportunity. This information makes it possible to develop players' decision making, enables coaches to design training drills based on simulated matches, and provide feedback to their players in order to elucidate the plays that can be most successful or to prevent opponent's plays that can offer most risk (Batista et al. 2019; Davids et al. 2013; Memmert et al. 2017). Further, it is possible to recognize players with similar displacement patterns for substitution, during the training of specific successful plays. The coach during the match can identify similarities between the current and past opponent teams in terms of the adopted strategies. Then, the most effective plays employed at that moment can be replayed. Recognising the displacement pattern of the most recurrent or successful plays, taking into account the pitch region where occurs, may provide even more relevant information about the determinants events of the match. Such results demonstrate the potential of spatiotemporal data exploration using the integration of knowledge between computer and sports scientists (Rein and Memmert 2016; Goes et al. 2020).

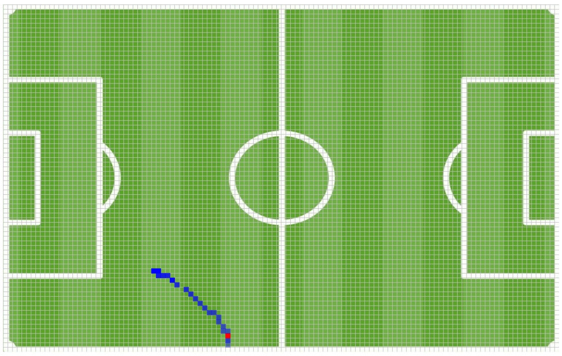


Fig. 14: Common dribbling using full-back player (left side) with a frequent itemset by positioning, using n=15. Red square is the exact point labelled as dribbling, the blue squares represent the previous and posterior positions after the successful dribbling.

5 Conclusions and Future Work

In this paper, we introduced a novel framework for sport action mining, called SAM framework, using the positional data of players. We model the problem of sports analysis using sequences of confidence levels computed from the player's displacements. Our framework takes advantage of an association rule mining algorithm for modelling actions in soccer by discovering frequent itemsets to generate association rules for finding patterns and thus recognise dribbling actions in soccer.

Experimental results demonstrated the effectiveness of our approach in detecting dribbling actions considering datasets composed of matches from different years and championships. Our framework was robust to characterise (through clustering) and detect (through classification) dribbling actions performed by players in different positions. These results pave the way for further studies about the effectiveness of play, the similarity between players, modelling match strategies, and scouting automatisation. All of these tasks are able to be performed online since after extracting the association rules, the matching step can be executed when acquiring the spatial position of players.We will focus on this kind of experiment in the sequence of this project.

Future research efforts will focus on evaluating different tactical strategies by modelling the displacement of several players. Furthermore, we intend to enrich the representation employed to describe each sport action, e.g., by modelling the position of the ball and opponents.

Acknowledgment

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